Simulation Approach to Warehouse Cost Minimization in Stochastic Environment

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The objective of inventory management is to balance conflicting goals like keeping stock levels down to have cash available for other purposes and having high stock levels for the continuity of the production. Simulation approach is used to minimize total warehousing cost while no stock-outs occur and warehouse capacity is not exceeded. A case study of replenishment process optimization is presented on several representative materials of an automotive company using two replenishment algorithms: fix review period and full capacity ordering. The presented simulation results indicate considerable cost reduction without violating the mentioned constraints. The fuzzy logic evaluator, a decision support system used for simulation results assessment, is presented and discussed.

Key words: inventory control, simulation, optimization, stochastic models, fuzzy sets, decision support system

Simulacijski pristop k minimiziranju stroškov skladišča v stohastičnem okolju

Cilj upravljanja z zalogami je uravnotežiti nasprotujoče si kriterije, npr. imeti na zalogi dovolj za kontinuirano proizvodnjo, hkrati pa imeti kar najnižje zaloge, da so finančna sredstva na voljo za druge namene. Predstavljen je simulacijski pristop za minimizacijo skupnih stroškov poslovanja skladišča ob dveh omejitvah: ne sme biti izpadov proizvodnje in kapaciteta skladišča ne sme biti presežena. Raziskava optimizacije procesa naročanja se je vršila na izbranih artiklih podjetja. Uporabljena sta bila dva algoritma naročanja: naročanje na stalne intervale in naročanje na polno kapaciteto skladišča. Predstavljeni simulacijski rezultati kažejo na pomembno zmanjšanje stroškov brez kršitev zastavljenih omejitev. Opisan je sistem za podporo odločanju, t.j. ocenjevalec simulacijskih rezultatov na podlagi mehke logike.

Ključne besede: kontrola zalog, simulacija, optimizacija, stohastični modeli, mehke množice, sistem za podporo odločanju

1 Introduction

In an organization even with moderate size, there may be thousands of inventory stock keeping units and the main warehouse task is to enable the undisturbed production by assuring the right amount of materials. Several different principles of warehouse optimization are described in (Silver et al., 1998; Tompkins and Smith, 1998; Ljubič, 2000). One way of optimizing the warehouse process is to find the right replenishment strategy, while reducing the cost of the warehousing processes to a minimum without stock-outs occurring and warehouse capacity being exceeded. Therefore, the operator is dealing with the decision problem – when to order and how many? This decision problem is vast, especially if we consider the fact, that he has to find the right replenishment strategy for more than 10.000 components stored in the warehouse. Here the help of decision support system (DSS) is crucial as warehouse operators mainly use only their experience and intuition.

Decision making inherently involves consideration of multiple objectives and uncertain outcomes; and in many situations, we have to take into account both the outcomes of current decisions and future decision opportunities. Decision processes under uncertainty deal with the optimization of decision making under uncertainty over time. Problems of this type have found applications in a variety of decision contexts in different industries, including manufacturing, R&D management, finance, transportation, power systems, and water management. Manufacturing firms operate in an environment in which such factors as product demand and technology evolution inevitably involve uncertainty. Production planning and inventory control are operational level decisions that firms must make on a regular basis. Effective inventory control is important to managing cost by properly balancing various costs such as inventory carrying costs and transportation costs. Capacity planning is also the crucial part of strategic level decision making in the manufacturing and service industry. Complications arise in decisions on timings and sizes of investments in capacity due to the uncertain demand for capacity, e.g., customer demand, and availability of capacity, e.g., technology development. All of these factors, along with the significant and long-term impact of capacity decisions, make capacity planning one of the most important yet complex decisions for most industries (Cheng et al., 2005).

In supply chain organization, the main difficulty relates to system complexity. Many different viewpoints have to be considered, from legal agreements to technical constraints. To deal with such a complexity, most decision support systems are based on simulation tools (Arda and Hennet, 2004). Among specialists, it is widely accepted that mathematical or analytical modeling techniques are not sufficient if a detailed analysis is required of complex systems. The major weaknesses in using mathematical or analytical methodologies are (Wang and Chatwin, 2004):

- When analyzing a complex system, stochastic elements cannot be accurately described by a mathematical model and cannot be evaluated analytically as modern systems consist of many operations that occur randomly and nonlinearly. Therefore, the objective function may not be expressible as an explicit function of the input parameters; hence, mathematical models or other methods are impractical.
- Dynamic systems involve randomness that changes with time, such as an assembly line, where the components being assembled change with time. The modeling of complex dynamic systems theoretically requires too many simplifications, and the emerging models may not, therefore, be valid.
- Purely analytical methods are often insufficient for optimization because a mathematical model can only be built based on simplifying assumptions; therefore, accuracy often becomes a major problem for system optimization.

In some cases, one must resort to simulation even though in principle some systems are analytically tractable; that is because some performance measures of the system have values that can be found only by running a simulation model or by observing an actual system. Consequently, the analytical effort required to evaluate the solution may be so formidable that computer simulation is the only realistic option. Instead of using experts to build an extensive mathematical model by using the analytical approach, computer-based simulation is used where the method of analyzing the system is purely theoretical. Computer-based simulation is seen as an integral business tool giving flexibility and convenience in designing, planning and analyzing complex processes and/or systems. This is because computer-based modeling and simulation methods have the capability of representing the complex static structure as well as the dynamic behavior of systems (Wang and Chatwin, 2004; Kljajić et al., 2000).

Clearly, the imaginative and disciplined application of dynamic modeling and simulation provides a potentially useful mechanism through which managers can gain a comprehensive understanding of system behavior, concentrating on core business processes such as order fulfillment, product development as well as customer acquisition, satisfaction, and retention. However, the means by which management in general and senior management in particular make decisions can, in itself, also be regarded as a core value-adding process that impacts fundamentally upon the overall effectiveness of the organization (Fowler, 2003).

This paper presents the simulation model based on system dynamies methodology (Forester, 1961), used to solve replenishment strategy problems (when to place an order and how many products to order) in a medium-sized company in order to improve its warehousing processes. Previous research is described in (Kofjač and Kljajić, 2004).

2 Warehouse model

2.1 The warehouse problem formulation

Dealing with problems of warehousing, we encounter several contradictory criteria. An overly large warehouse means a greater amount of stock, greater capital cost and more staff. The space itself is very valuable today. An overly small warehouse can represent possible stock-outs, it demands a reliable supplier etc.

Products stored in a warehouse also play an important role in a process of optimization of warehousing processes. They belong to different categories according to ABC and XYZ classification. ABC classification divides products into three categories according to their value, while XYZ classification divides products into three categories according to the dynamics of their consumption (Silver et al., 1998; Ljubič, 2000). The dynamics of product consumption and the products value must be taken into consideration in order to improve the warehousing processes. We believe that there is a lack of optimization technology in use and that there are a number of possibilities of how to improve the warehousing processes. The warehouse personnel solve the complex problems mostly by using their experience, without the use of optimization techniques.

Our goal is to rationalize the warehouse replenishment process, this means determining the interval between orders and the quantity to be ordered, so that the warehouse will operate with minimal common costs. Cost function includes:

- fixed ordering costs,
- transportation costs,
- costs of taking over the products,
- costs of physical storage,
- cost of capital.

The following limitations have to be taken into consideration:

- maximal warehouse capacity for a specific product must not be exceeded,
- no stock-outs may occur.

In this case we are dealing with a warehouse used for storing components for further build-in. The lead time for some products delivered into the warehouse is stochastic within an interval [t_{dmin}, t_{dmax}]. The problem occurs in defining ordering quantity, because past orders must be considered as well as the average consumption of a specific product. Long lead times also represent a problem, because they are usually much longer than the time period in which the consumption plan can be predicted with a certainty. Therefore, the variability of a production plan has to be considered. Unlike deterministic models, stochastic models do not necessarily give the same output for the same input. Within a stochastic model there will be at least one variable that is not known with certainty (Oakshott, 1997). In this case the variables are the consumption plan and lead times.

A consumption plan is planned for 24 weeks and can be predicted with a certainty, e.g. for six weeks. After this period, a consumption plan uncertainty factor (e.g. 3%) must be considered every two weeks. Therefore, a safety factor, which increases the ordering quantity, must be considered when placing an order (e.g. 10%).

2.2 CLD of the warehouse process and its simulation model implementation

Figure 1 represents the causal loop diagram (CLD) from which the influences of the warehouse model elements can be observed. The arrow represents the direction of the influence and the + or – sign its polarity.

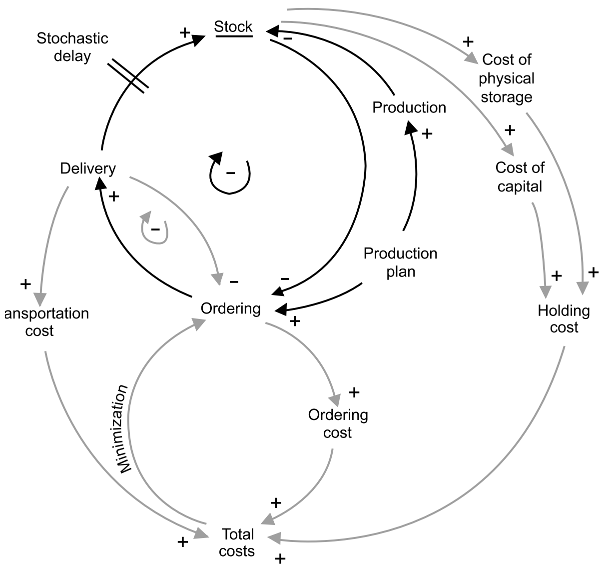

Figure 1: Causal loop diagram of the warehouse model

Delivery impacts *Stock* and *Transportation Costs*. If the amount of *Delivery* increases above what it would have been, the *Stock* and *Transportation Costs* are increased above the initial value. The increased value of *Stock*, increases *Cost of physical storage* and *Cost of capital*, but it decreases *Ordering quantity*. If the quantity of *Production plan*, which represents the reference value, is increased, *Consumption* and *Ordering quantity* are both increased. The increased value of *Consumption* decreases *Stock*. If the *Ordering quantity* is increased, the *Delivery* and *Fixed ordering cost* are both increased. The increased values of *Cost of physical storage* and *Cost of capital* increase the value of *Holding cost*, which increases the value of *Total cost* together with *Fixed ordering cost* and *Transportation cost*.

There are two negative feedback loops in the causal loop diagram. The first interconnects *Stock*, *Ordering* and *Delivery* and it represents the fact that we order less if the stock level is high. The second interconnects *Delivery* and *Ordering* and represents the concept that we order less if we have ordered more before. This loop takes into account orders which haven't been delivered yet and will have impact on the stock level later on.

Figure 2 shows the warehouse simulation model built with Matlab (submodels are excluded). Matlab was chosen because it supports simulation with Simulink and offers a powerful computational engine, which provides a quick execution of the simulation runs.

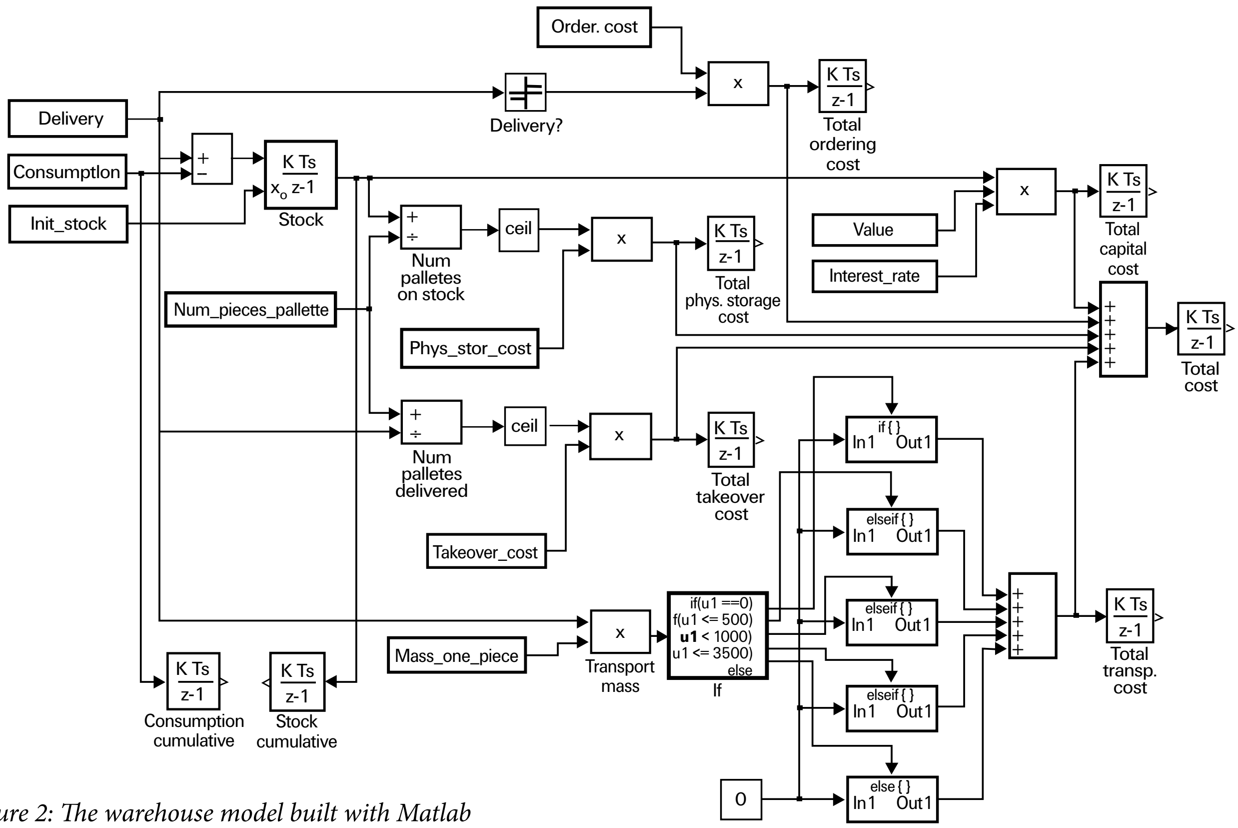

Figure 2: The warehouse model built with Matlab

3 Replenishment algorithms

Two replenishment algorithms were applied in the simulation model in order to find an ordering strategy which would produce less common costs: a model with fix review period and a full capacity ordering model.

3.1 Fixed review period algorithm

The Fixed review period algorithm (FRP) is similar to the (R, S) system (described in Silver et al., 1998), where, every R units of time, an order is made to adjust the stock level to the order-up-to-level S. In contrast to the (R, S) system, S is not a fixed value in the FRP algorithm. The FRP is based on making a sum of consumption for a specific material over a specific period (fixed) of time. The quantity of this sum is used in order quantity calculation together with the past orders and stock-on-hand. This model is appropriate for products with great warehouse capacity.

3.2 Full capacity ordering algorithm

The Full capacity ordering algorithm (FCO) is similar to the FRP and the (s, S) system (described in Silver et al., 1998). Replenishment in the (s, S) system is made whenever the stock level drops to the order point s or lower and variable replenishment quantity is used, ordering enough to raise the stock level to the order-up-to-level S. In comparison to the (s, S) system, the s is omitted in FCO. The consumption for a specific material is not summed for a fixed review period (like in the FRP algorithm); instead the consumption is summed until we reach the maximum warehouse capacity (S) for a specific material. This algorithm is appropriate for materials with very limited warehouse capacity. This algorithm is not used if the capacity is unknown.

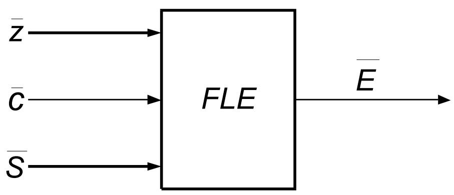

Figure 3: Fuzzy logic evaluator

4 Fuzzy logic evaluator

Several factors in the supply chain are hard to evaluate, e.g. shortage cost, supplier's reliability etc. In some cases, it is possible to evaluate e.g. supplier's reliability only linguistically by saying that supplier is "very reliable" or "sometimes reliable". Since those are only soft descriptions, fuzzy logic (Zadeh, 1965) is often used to assess such linguistic descriptions. In our case, the shortage cost is unknown; only the number of stock-outs is known. The fuzzy number of stock-outs, together with fuzzy highest stock level and fuzzy total cost, is used to assess the results of each simulation scenario.

The fuzzy logic evaluator (FLE) is presented in Figure 3. The inputs of the FLE are the crisp arrays of number of stock-outs ($\overline{C}$), total costs ($\overline{Z}$) and highest stock levels ($\overline{S}$). The array contains e.g. the number of stock-outs for each simulation scenario. The arrays are normalized in the interval [0, 1] and then fuzzified using equally spaced gaussian membership functions (MFs) as shown in Table 1.

The FSA inference system contains the expert's rule base consisting of 125 (= 5^3) rules. Estimation of the i^{th} replenishment strategy is calculated according to the eqn. 1:

$$\textbf{If } Z_i \textbf{ and } C_i \textbf{ and } S_i \textbf{ then } E_i,\ i = 1, 2, \ldots n \tag{1}$$

where n is a number of simulation scenarios. The output of the FLE is the array of scenario assessments, $\overline{E}$ which is defuzzified using a *Som* (smallest value of minimum) function in the range [0, 1]. The scenario, i.e. replenishment algorithm, with the lowest grade is suggested as the most suitable.

5 Results

The experiment was performed with the historic data provided by the observed company. Altogether, nine materials were examined in this study and their details are presented in Table 2.

The simulation of the actual warehouse process (RP – Real Process) was using real data of delivery and demand, while the simulation with replenishment algorithms (VP – Virtual Process) was using only real demand data. The ordering and delivery process in VP were controlled by replenishment algorithms. The RP simulation was run only once, whereas ten simulation runs were executed

Table 1: FLE membership functions

Variable	Membership functions				
Z	none	few	some	many	a lot
S	very low	low	middle	high	very high
C	very low	low	middle	high	very high
E	excellent	very good	good	poor	very poor

Table 2: The materials details – classification, capacity and lead-times

Case	Classification	Capacity (piece)	Lead-time (week)
1	BY	200000	6-8
2	AX	-	5-6
3	BY	-	5-6
4	AZ	-	5-6
5	AY	-	6-7
6	BZ	-	6-7
7	AY	120000	5-6
8	BX	-	6-7
9	AZ	70000	14-16

for every VP replenishment algorithm. Based on these simulation runs, average costs and average stock-outs were calculated. With several simulation runs and a calculation of average values, we have tried to minimize the influences of the random generator, which represents the stochastic environment. Out of all simulation runs the maximum stock level was considered and the strategy with minimum highest stock level is favored. A Monte Carlo simulation was used for variation of production plan unreliability. The production plan variability was simulated by perturbations of its quantity every 2 weeks for a certain amount, e.g. 5%. Variable lead times are simulated by uniform random generator. If stock-outs occurred during the simulation, the missing quantity was transferred into the next period. The safety stock was also considered; it was equal to the average weekly demand.

Table 3: The replenishment algorithms simulation results for stock-outs (Z), highest stock level (S) and total cost (C) for the observed cases

Case		Real	FRP 2 week	FRP 3 week	FRP 4 week	FRP 5 week	FRP 6 week	FRP 7 week	FRP 7 week	FRP 9 week	FRP 10 week	FCO
1	Z*e^{0}	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	***0,00***
	S*e^{5}	1,44	2,17	2,09	2,28	2,31	2,37	2,59	2,53	2,56	2,55	***2,00***
	C*e^{6}	1,03	1,63	1,57	1,63	1,62	1,60	1,65	1,64	1,66	1,64	***1,38***
2	Z*e^{1}	0,00	0,00	0,00	0,00	0,00	***0,00***	0,00	0,00	0,00	0,00	
	S*e^{3}	4,32	1,30	1,58	1,52	1,74	***1,85***	1,89	2,05	2,51	2,86	
	C*e^{6}	2,50	1,40	1,34	1,28	1,24	***1,23***	1,24	1,26	1,29	1,29	
3	Z*e^{1}	0,00	0,00	0,00	0,00	0,00	***0,00***	0,00	0,00	0,00	0,00	
	S*e^{3}	4,95	0,89	1,27	1,44	1,46	***1,48***	1,47	2,20	1,62	1,93	
	C*e^{6}	3,21	1,14	1,06	1,02	0,98	***0,94***	0,96	1,03	1,04	1,03	
4	Z*e^{1}	0,00	***0,00***	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	
	S*e^{3}	4,48	***4,02***	4,29	5,41	5,48	5,99	6,71	7,67	7,78	8,97	
	C*e^{6}	2,32	***1,69***	1,71	1,78	1,81	1,90	1,92	2,17	2,16	2,21	
5	Z*e^{0}	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	***0,00***	
	S*e^{3}	6,25	4,75	4,95	5,99	5,91	6,15	5,76	6,61	6,81	***7,52***	
	C*e^{6}	8,59	9,65	9,69	8,56	7,73	8,37	7,97	7,42	7,41	***7,23***	
6	Z*e^{0}	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	***0,00***	
	S*e^{3}	1,21	1,10	1,25	1,88	1,83	1,48	1,87	2,76	2,77	***2,03***	
	C*e^{5}	2,65	3,02	3,10	2,94	2,88	2,75	2,89	2,86	2,76	***2,71***	
7	Z*e^{0}	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	***0,00***
	S*e^{5}	1,04	2,06	2,06	2,30	2,21	2,23	2,26	2,33	2,43	2,38	***1,20***
	C*e^{6}	2,75	1,83	1,87	1,95	1,88	1,94	1,94	2,00	2,00	1,97	***1,83***
8	Z*e^{0}	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	***0,00***	
	S*e^{3}	1,26	0,82	0,97	0,92	0,99	1,24	1,32	1,40	1,42	***1,51***	
	C*e^{6}	1,67	1,76	1,56	1,45	1,33	1,22	1,16	1,13	1,12	***1,05***	
9	Z*e^{1}	0,00	0,00	0,00	0,00	0,00	0,00	***0,00***	0,00	0,00	0,00	0,00
	S*e^{4}	2,07	4,72	5,13	5,41	5,69	6,34	***6,17***	7,30	7,37	7,81	7,00
	C*e^{6}	6,77	5,81	5,58	5,21	4,78	4,62	***4,59***	4,73	4,55	4,64	4,89

Table 4: The achieved savings of the VP regarding the RP

Case	RP total cost	VP total cost	Savings	The best VP strategy
1	$1{,}03 \cdot e^6$	$1{,}38 \cdot e^6$	33,9	FCO
2	$2{,}50 \cdot e^6$	$1{,}23 \cdot e^6$	50,8	FRP - 6
3	$3{,}21 \cdot e^6$	$0{,}94 \cdot e^6$	70,7	FRP - 6
4	$2{,}32 \cdot e^6$	$1{,}69 \cdot e^6$	27,2	FRP - 2
5	$8{,}59 \cdot e^6$	$7{,}23 \cdot e^6$	15,8	FRP - 10
6	$2{,}65 \cdot e^5$	$2{,}71 \cdot e^5$	2,3	FRP - 10
7	$2{,}75 \cdot e^6$	$1{,}83 \cdot e^6$	33,5	FCO
8	$1{,}67 \cdot e^6$	$1{,}05 \cdot e^6$	37,1	FRP - 10
9	$6{,}77 \cdot e^6$	$4{,}59 \cdot e^6$	32,2	FRP - 7[1]

Simulation results are shown in Table 3, where the "Real" column represents simulation results of the RP, while the other columns represent results of the VP. The VP strategy producing the best results, as assessed by FLE, is indicated in bold and italics for each case. The research team verified the FLE assessments.

The summary of replenishment process optimization is presented in Table 4. No stock-outs occurred in any case and significant total cost savings were achieved with almost all cases, except for Cases 1 and 6, where VP replenishment algorithms could not achieve any savings; on the contrary, these algorithms yielded higher total costs – 33,9% for Case 1 and 2,3% for Case 6. Obviously, the warehouse operator has been using a better replenishment method than the one proposed by VP replenishment algorithms.

The FCO algorithm yielded the best results for the Cases 1 and 7, where capacity is known; all other VP replenishment strategies exceeded the warehouse capacity for these two cases, thus violating the capacity restriction. Capacity is also known for Case 9, but in this case the "FRP 7 weeks" algorithm was chosen as the one producing the best results. Although "FRP 9 weeks" produced lower

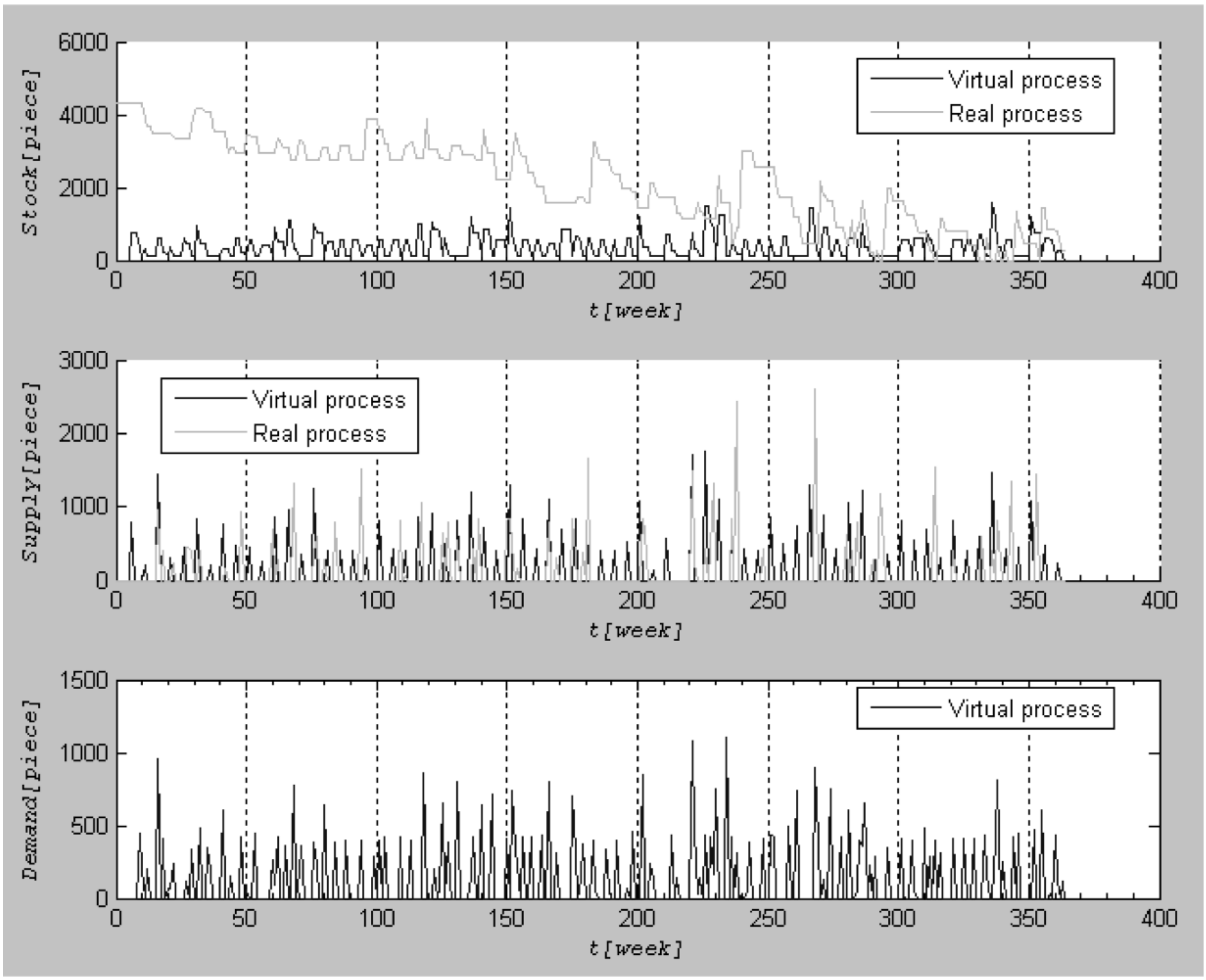

Figure 4: Comparison of stock-on-hand, supply and demand dynamics for the RP and the VP for a specific case

total cost than "FRP 7 weeks", it also violated the capacity restriction.

Figure 4 presents simulation results for the RP and VP for a specific case. The RP is represented by a brighter line and the VP by a darker line. The first graph presents stock level dynamics, the second delivery dynamics and the third the consumption dynamics throughout simulation time. The results shown can be used to indicate similarities or differences between the two processes. The supply dynamics graph indicates some similarities in the ordering strategy – some peaks (representing order quantity) are very similar but with some time delay. The simulator also allows us to compare two methodologies used in the ordering process: heuristics of the warehouse operator and algorithm based on simulation. From the Figure 4 one can observe, from the stock level dynamics, the operators' "learning by experience". Namely, starting from high stock level, the operators' replenishment strategy slowly improves over time approaching optimal strategy obtained by simulation. From the obtained results we can deduce about the usefulness of simulation method for the operator training for the new replenishment strategy.

Figure 5 shows frequency distribution comparison for the ordering quantities and the intervals between two consecutive orders. In the upper diagram, one can notice ordering quantities similarities between the RP and the VP with majority around 500 pieces per order. The lower diagram points towards a big difference between ordering intervals; the RP's intervals are scattered throughout the diagram, while the VP's intervals have a predominant value at five weeks.

The analysis presented in Figure 4 and Figure 5 allows in-depth insight into the reasons for the total cost reductions. From Figure 4, one can assume that cost savings of the VP are mainly due to the much lower cost of capital, because of much lower cumulative stock-on-hand. On the other hand, Figure 5 might point towards the non-optimal reorder timing of the RP. Obviously, the observed case needs a strict replenishment policy with a fixed review period instead of the frequently changing policy used by the warehouse operator.

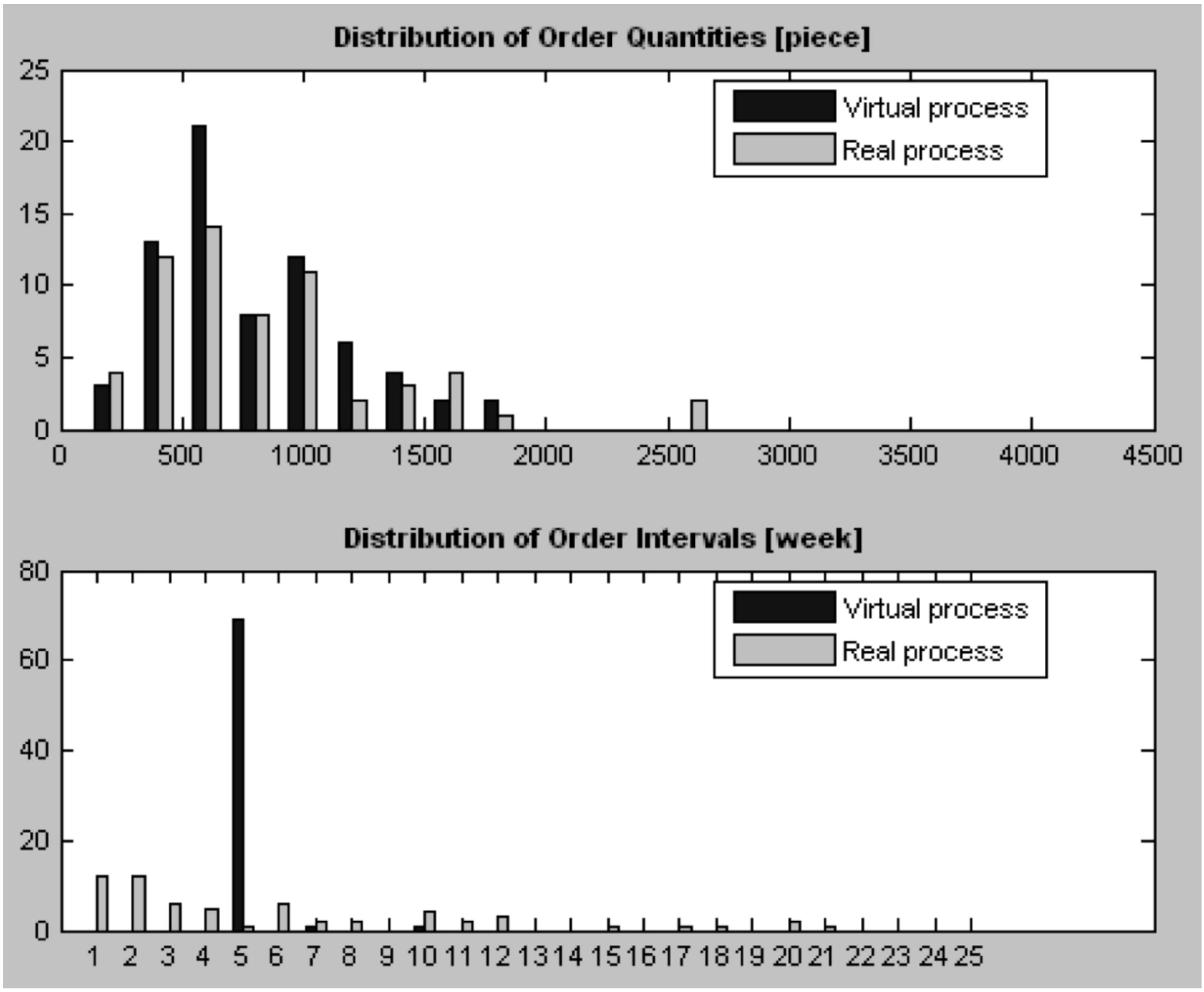

Figure 5: Comparison of ordering quantity and ordering intervals frequency distribution for a specific case

6 Conclusion

This paper researched the warehouse stock optimization using two optimization algorithms. The SD approach was used in modeling and validation of the warehouse model. The simulation model was built using Matlab – Simulink. The observed company's representative cases were analyzed and the simulation results show potential since a cost reduction of a few percents is usually considered a success. Nevertheless, the simulation model still needs to be validated meticulously, although the logical validation was already accepted by the research team.

The advantage of optimization with presented methods was in its speed with which we have achieved the results. The solution is available almost instantly and this is very important as the staff is usually under severe pressure and that makes the decision process more difficult, result in them making more mistakes. The FLE proved as a reliable decision support system in suggesting the proper replenishment algorithm, thus taking some more pressure off the staff. The consequence is the near-optimal material quantity in the warehouse, which assures undisturbed production and minimal holding costs.

Management today is faced with more decision factors than they feel they can cope with. Managers face great uncertainty about the operating environment and what could happen as a consequence of various decisions. The simulator presented in this paper can simulate various scenarios, undertake "what-if" analyses and help to determine potential outcomes and strategies, so as to reveal the truly best options.

Since the simulation results are promising, the research is still in progress in a way to fully implement inventory control decision support system in the company. Nevertheless, the presented simulator is useful as a learning tool for the warehouse operator to learn about new replenishment policies.

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